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COMPARATIVE STUDY OF MAXIMUM POWER POINT TRACKING USING LINEAR KALMAN FILTER & UNSCENTED KALMAN FILTER FOR SOLAR PHOTOVOLTAIC ARRAY ON FIELD PROGRAMMABLE GATE ARRAY

Varun Ramchandani[a*], Kranthi Pamarthi[b], Shubhajit Roy Chowdhury[a]

[a] Center for VLSI and Embedded Systems Technology, IIIT Hyderabad, Hyderabad, India

[b] Dept. of Electronics& Communication Engineering, NIT Rourkela, Rourkela, India

Emails: [a]varun.ramchandaniug08@studens.iiit.ac.in, src.vlsi@iiit.ac.in, [b]109ei0083@nitrkl.ac.in

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ABSTRACT: ***The paper proposes comparative study of Field Programmable Gate Array implementation of 2 closely related approaches to track maximum power point of a solar photovoltaic array. The current work uses 2 versions of kalman filter viz. linear kalman filter and unscented kalman filter to track maximum power point. Using either of these approach the maximum power point tracking (MPPT) becomes much faster than using the conventional Perturb & Observe approach specifically in case of sudden weather changes. In this paper comparative analysis of both the algorithms being implemented on FPGA is presented. Experiments have been performed under optimal conditions as well as under cloudy conditions i.e. falling irradiance levels. Using the linear kalman filter the maximum power point of a solar PV array has been tracked with an efficiency of 97.11% while using the unscented kalman filter technique the maximum power***

point of the same solar PV array is tracked with higher efficiency of 98.3%. However, the maximum power point has been tracked at a much faster rate i.e. 4.5 ms using the linear kalman filter approach as compared to the unscented kalman filter approach which tracks maximum power point at 11 ms which is in turn faster than existing generic Perturb and Observe approach which takes 15ms to track the maximum power point . The system has been implemented on Altera EP2C20F484C7 FPGA board.

Index Terms: Maximum Power Point Tracking (MPPT), Kalman Filter, Unscented Kalman Filter, Perturb and Observe (P&O), Photovoltaic (PV), FPGA.

1. INTRODUCTION

In today's world renewable energy sources play important role in electricity generation. Several sources like wind, solar, biogas etc are important energy sources. Energy from the sun is the best option for renewable energy as it is available almost everywhere and is free to harness. Solar radiation from the sun is converted to electrical energy by using solar cells which exhibit photovoltaic effect. These PV systems are available either as stand alone or as grid connected configurations. However, for PV systems the amount of electric power generated changes continuously with weather conditions. In general, V-I curve for a PV array is non – linear so a specific point on the curve namely maximum power point needs to be tracked so that the whole system operates at maximum efficiency and produces maximum output power. Hence, Maximum Power Point Tracking (MPPT) algorithm is used for extracting maximum power available from a PV module under different conditions [1].

Out of numerous available techniques the one that is used most widely and commonly is Perturb & Observe (P&O) algorithm. Fig. 1 shows how power is calculated using P&O algorithm. P&O is also called as hill climbing method because it checks the rise of the curve till MPP and the fall after that point. Using P&O algorithm the controller adjust voltage and measures power and if this measured power is greater than the previous value of power, adjustments are made in the same direction until there is no more increment in power [2]. This method is easy to implement but can cause oscillations in power output and can sometimes show tracking failures in rapid environmental changes [3] i.e. locates operating point away from MPP when there is a sudden change in voltage characteristics.

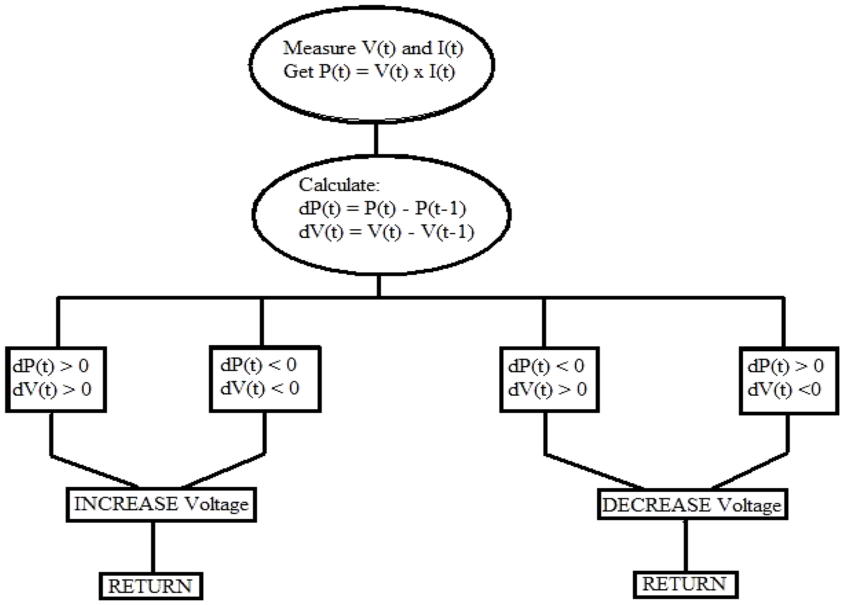

Figure 1. Flowchart depicting the Perturb & Observe algorithm

This paper proposes implementation of a new MPPT technique using two versions of Kalman Filter. First one being the Linear Kalman Filter algorithm to track maximum power point and another one is by using Unscented version of Kalman Filter which is especially used for non-linear systems. The algorithms are implemented on Altera Cyclone II EP2C20F484C7 FPGA [4].

The paper is organized as follows. Section 2 describes the characteristics of a PV array. Section 3 describes both the Kalman filter approaches for tracking maximum power point. Section 4 describes the system configuration and setup. In section 5 comparative results of MPPT using both the approaches on FPGA are discussed and Section 6 gives the conclusion.

2. CHARACTERISTICS OF PV ARRAY

PV array consists of collection of numerous solar cells in series or parallel to get the desired voltage and current. Fig. 2 shows the equivalent circuit model of a solar cell. Rsh is very large, Rs is very small and both can be ignored in order to simplify the electrical model.

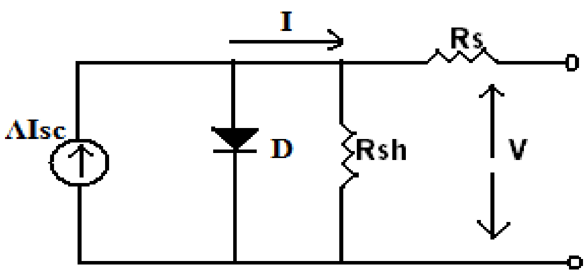

Figure 2. Solar cell equivalent circuit

The simplified equation [5] to describe the PV panel is given as

$$I = I_{SC}\left\{\lambda - \frac{1}{\exp\left(\frac{qA}{kT}\right)}\left(\exp\left(\frac{qAV}{kTV_{OC}}\right)-1\right)\right\} \tag{1}$$

where V_{oc} and I_{sc} are open circuit voltage and current values at 1kW/m^2 and 25^{0}C. T is the temperature of array in ^{0} C, q is the elementary charge, k is the Boltzmann constant, λ is irradiance in kW/m^2 and A is a constant, generally taken as 0.2464. V and I are the array output voltage and current.

A general I-V curve is shown in the Fig. 3 (a) under given conditions i.e. irradiance of 1kW/m^2 and temperature of 25^{0}C there is one point on the I-V curve which gives Maximum Power Point because it maximizes the area under the curve. A general P-V curve is shown in Fig. 3 (b).

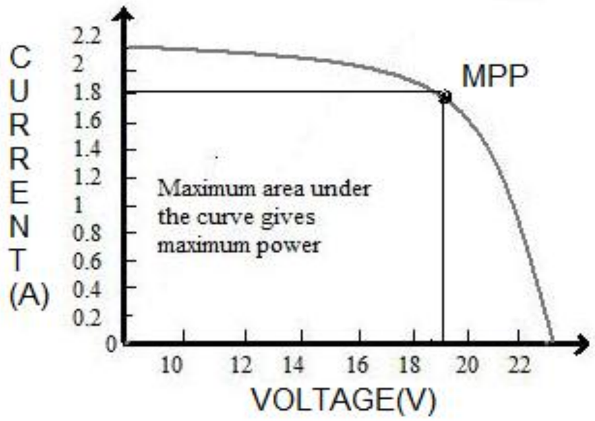

Figure 3 (a)

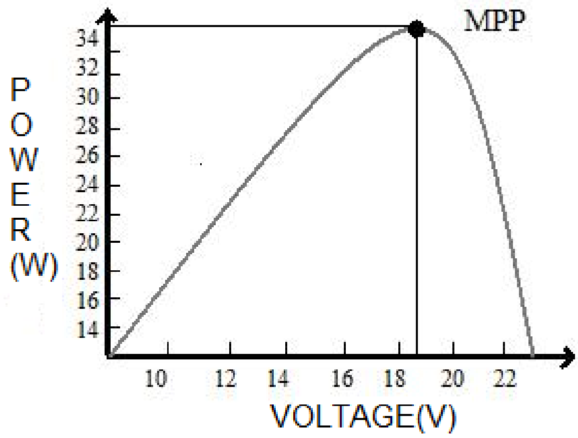

Figure 3 (b)

Figure 3. (a) Generic Current vs. Voltage curve; (b) Generic Power vs. voltage curve

3. MPPT USING KALMAN FILTER

3.1. KALMAN FILTER

Kalman filter provides stochastic estimation in noisy environment. The kalman filter operates on estimating states by using recursive time updates & measurement updates over time. Noise effect in the system is decreased due to recursive cycles which finally lead to the true value of measurement [6]. Fig. 4 shows the generic block diagram of Kalman Filter.

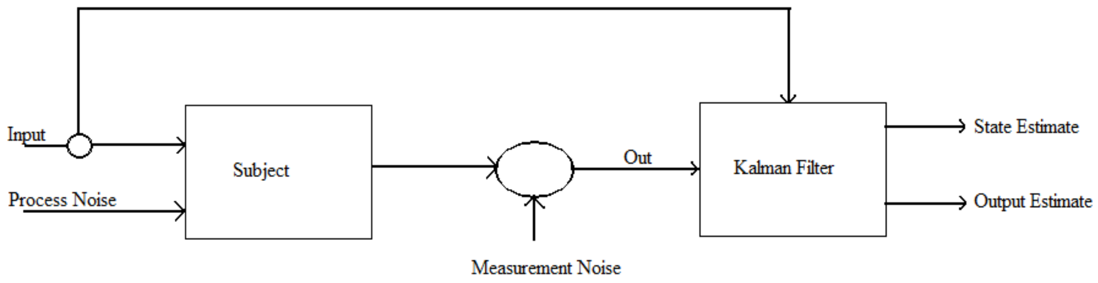

Figure 4. Generic block diagram to describe Kalman Filter algorithm

Let the input be x_t at iteration t, control process be u_t at iteration t, w be the added process noise and v be the added measurement noise.

Then the Linear Kalman filter [7] equations are given as follows.

3.1.1. TIME UPDATE (PREDICTION STATE)

$$\hat{x}_t^- = A\,\hat{x}_{t-1} + B u_{t-1} \tag{2}$$

$$z_t^- = A z_{t-1} A^T + Q \tag{3}$$

Here Q is the process noise covariance, $\hat{x}_t^-$ be the state estimate at iteration t given by the results from former iterations, $\hat{x}_{t-1}$ be the state estimate at iteration t given by the measurement output y^t , z_t^- be the priori error covariance and z_t (z_{t-1}) be the posteriori error covariance**.** A & B are constants. And according to equation (3), z_t is similar to z_{t-1}.

3.1.2. MEASUREMENT UPDATE (CORRECTION STATE)

$$K_t = z_t^- C^T (C z_t^- C^T + R)^{-1} \tag{4}$$

$$\hat{x}_t = \hat{x}_t^- + K_t(y_t - C\hat{x}_t^-) \tag{5}$$

$$z_t = (I - K_t C) z_t^- \tag{6}$$

where R is the measurement noise covariance, K_t is the Kalman gain & C is constant.

The above equations [8] represent kalman filter implementation for a generic linear discrete system. The time update predicts forward state estimate and error covariance. The estimates are then put into measurement update which acts as correction mechanism and correct the estimated values. As the above cycle takes place multiple times turn by turn the noises are reduced and the error covariance z_t becomes closer and closer to zero.

3.2. MPPT USING LINEAR KALMAN FILTER APPROACH

According to the P – V curve of a solar photovoltaic cell, power increases with a gradual positive slope until reaches one optimal point and decreases after that steeply. Based on that feature the MPPT algorithm is governed by the given state equation [9] where V_{actual}^{t+1} is the value of voltage updated by the MPPT controller at iteration t+1.

$$V_{actual}^{t+1} = V_{actual}^{t} + M\frac{\Delta P^t}{\Delta V^t} + w, \quad (A=1 \text{ and } B=M) \tag{7}$$

M is the step size corrector and $\Delta P^t/\Delta V^t$ denotes the slope of the P – V curve at instant t of solar array. The slope $\Delta P^t/\Delta V^t$ is same as control unit u_t and on adding process noise w into the system a similar one dimension linear state space equation can be formed.

The measurement equation is dependent on V_{actual}^{t} and measurement noise v.

$$y^t = V_{actual}^{t} + v, \ (C=1) \tag{8}$$

Considering y^t as the reference voltage at given instant we get the updated measurement equation [10] as

$$V_{ref}^{t} - V_{actual}^{t} = v \tag{9}$$

Two known values, V_{ref}^{t} and $\Delta P^t/\Delta V^t$ are used for Kalman filter estimate.

3.2.1. TIME UPDATE

Based on voltage estimate V_{actual}^{t-1} & error covariance z_{t-1} of the previous state we predict new estimate

$$V_{actual}^{t^-} = V_{actual}^{t-1} + M\frac{\Delta P^{t-1}}{\Delta V^{t-1}}, \quad (V_{actual}^{t^-} \text{ is analogous to } \hat{x}_t^-)$$
$$z_t^- = z_{t-1} + Q \tag{10}$$

3.2.2. MEASUREMENT UPDATE

From the error covariance update in prediction (time update) state we initially calculate the Kalman gain:

$$K_t = z_t^-(z_t^- + R)^{-1} \tag{11}$$

Now K_t updates the estimate of V_{actual}^{t} and z_t by using $V_{actual}^{t^-}$ and z_t^- from the prediction state & K_t from equation (11)

$$V_{actual}^{t} = V_{actual}^{t^-} + K_t(V_{ref}^{t} - V_{actual}^{t^-}) \tag{12}$$

$$z_t = (1-K_t)z_t^- \tag{13}$$

As the above steps occur turn by turn the estimated result is expected to be closer to the maximum power point.

Making the similar system to be non linear we will be going for Unscented Kalman Filter (UKF). We could have used Extended Kalman filter (EKF) which is the most common approach for the non linear systems. However, in UKF the non linear functions of the system & measurement models are not approximated as in EKF, they are estimated accurately to 2nd order for any non linearity. So we prefer UKF over EKF for implementation of MPP tracker here.

3.3 MPPT USING UNSCENTED KALMAN FILTER APPROACH

In UKF the state is represented using the Gaussian Random Variable and is specified using a set of chosen sigma points. Sigma points are deterministically chosen set of sample points which represent the state distribution. These sample points capture true mean & covariance of the Gaussian random variable when propagated though the system.

According to the function used in linear kalman filter we used $\Delta P^t / \Delta V^t$ as the control factor but here we will go for the instantaneous slope dP/dV of the P – V curve to get accurate filter response.

$$\frac{dP}{dV} = \frac{d(VI)}{d(V)} = I + V\frac{dI}{dV} \tag{14}$$

Now taking 'I' from the PV array characteristics as given by equation (1) we have

$$V\frac{dI}{dV} = \frac{-VI_{sc}}{e^{\frac{qA}{KT}}}\left\{\frac{qA}{KTV_{oc}} e^{\left(\frac{qAV}{KTV_{oc}}\right)}\right\} \tag{15}$$

where each of the parameters are same as defined in the case of linear kalman filter.

According to the P – V curve power increases with a gradual positive slope until reaches one optimal point and decreases after that steeply. Based on that feature the MPPT algorithm is governed by the given state equation [8] where V_{actual}^{t+1} is the value of voltage updated by the MPPT controller at iteration t+1.

$$V_{actual}^{t+1} = V_{actual}^{t} + M\frac{dP^t}{dV^t} + w, \quad (A=1 \text{ and } B=M) \tag{16}$$

Now, consider propagating a random variable "V" (dimension L) with mean $\hat{V}$ & covariance Z_v through a non linear function y = f(v). The sigma points are calculated for the function by the following set of equations [11]:-

$$\lambda = \alpha^2(L+k) - L \tag{17}$$

$$W_0^m = \lambda / (L+\lambda) \tag{18}$$

$$W_0^c = W_0^m + (1-\alpha^2+\beta) \tag{19}$$

$$W_i^c = W_i^m = 1 / 2(L+\lambda); (i = 1,2,3...,2L) \tag{20}$$

$$V_{t-1|t-1}^0 = \hat{V}_{t-1|t-1} \tag{21}$$

$$V_{t-1|t-1}^i = \hat{V}_{t-1|t-1} + \sqrt{[(L+\lambda)Z_{t-1|t-1}]_i}\ ; i = 1, 2, 3, \ldots, L \tag{22}$$

$$V_{t-1|t-1}^{i+L} = \hat{V}_{t-1|t-1} - \sqrt{[(L+\lambda)Z_{t-|t-1}]_i}\ ; i = L+1, L+2, L+3, \ldots, 2L \tag{23}$$

where α is the spread of sigma points around the mean $\hat{V}$, k being the scaling parameter which is either 0 or 3-L , β incorporates prior knowledge of distribution of k, $\sqrt{[(L+\lambda)Z_{t-1|t-1}]_i}$ is for the i[th] row or column (depending on the square root form) and W_i is the normalized weight associated with the i[th] point.

We have chosen L as 1 (V_t has non linear dependency only on the voltage measured in previous iterations), k = 2, β = 2 (for any Gaussian random variable), α^2 is calculated experimentally to be 1/6 so that λ comes to be -1/2. $W_0^m = -1, W_0^c = 11/6$ & $W_i^m = W_i^c = 1$. One cycle of UKF occurs as follows:

3.3.1. CALCULATION AND PROPAGATION OF SIGMA POINTS (PREDICTION)

The sigma points are calculated and propagated to obtain mean and covariance of the state as [12] follows, here $V_{t-1|t-1}^0$, $V_{t-1|t-1}^1$ & $V_{t-1|t-1}^2$ are spread of voltages calculated at time instant t-1 , $\hat{V}_{t-1|t-1}$ is the mean voltage calculated at instant t-1. $Z_{t-1|t-1}$ is the covariance calculated at instant t-1. $\widehat{V}_{t|t-1}$ is the predicted mean and $Z_{t|t-1}$ is the predicted covariance.

$$V^{0}_{t-1|t-1} = \widehat{V}_{t-1|t-1} \tag{24}$$

$$V^{1}_{t-1|t-1} = \widehat{V}_{t-1|t-1} + \sqrt{\frac{Z_{t-1|t-1}}{2}} \tag{25}$$

$$V^{2}_{t-1|t-1} = \widehat{V}_{t-1|t-1} - \sqrt{\frac{Z_{t-1|t-1}}{2}} \tag{26}$$

$$V^{i}_{t|t-1} = V^{i}_{t-1|t-1} + MI_{sc}\left[\lambda - \frac{1}{e^{\frac{qA}{KT}}}\left\{\frac{qA}{KTV_{oc}} e^{\left(\frac{qAV^{i}_{t-1|t-1}}{KTV_{oc}}\right)} + e^{\left(\frac{qAV^{i}_{t-1|t-1}}{KTV_{oc}}\right)} - 1\right\}\right] \tag{27}$$

$$\widehat{V}_{t|t-1} = \sum_{i=0}^{2L} W_i^{m} V^{i}_{t|t-1} \tag{28}$$

$$Z_{t|t-1} = Q_{t-1} + \sum_{i=0}^{2L} W_i^{c} [V^{i}_{t|t-1} - \widehat{V}_{t|t-1}][V^{i}_{t|t-1} - \widehat{V}_{t|t-1}]^{T} \tag{29}$$

3.3.2. UPDATE (CORRECTION)

The measurement sigma points are now calculated and the mean and covariance of the voltage is updated using the given equations [13] as follows, where V_t^{ref} the reference voltage at time instant t is. $Y^{0}_{t|t-1}$, $Y^{1}_{t|t-1}$ and $Y^{2}_{t|t-1}$ are the spread of sigma points for the output. $\widehat{Y}_{t|t-1}$ is the mean calculated using the given sigma points. Z_{YY} is auto covariance and is calculated with the help of measurement noise R_t. Z_{VY} is cross covariance and K_t is the unscented kalman gain.

$$V_t^{ref} = V_{t-1}^{ref} + M\frac{\Delta P}{\Delta V} \tag{30}$$

$$Y^{0}_{t|t-1} = V_t^{ref} \tag{31}$$

$$Y^{1}_{t|t-1} = V_t^{ref} + \sqrt{\frac{[Z_{t|t-1}]}{2}} \tag{32}$$

$$Y^{2}_{t|t-1} = V_t^{ref} - \sqrt{\frac{[Z_{t|t-1}]}{2}} \tag{33}$$

$$\widehat{Y}_{t|t-1} = \sum_{i=0}^{2L} W_i^{m} Y^{i}_{t|t-1} \tag{34}$$

$$Z_{YY} = R_t + \sum_{i=0}^{2L} W_i^{c} [Y^{i}_{t|t-1} - \widehat{Y}_{t|t-1}][Y^{i}_{t|t-1} - \widehat{Y}_{t|t-1}]^{T} \tag{35}$$

$$Z_{VY} = R_t + \sum_{i=0}^{2L} W_i^{c} [V^{i}_{t|t-1} - \widehat{V}_{t|t-1}][Y^{i}_{t|t-1} - \widehat{Y}_{t|t-1}]^{T} \tag{36}$$

$$K_t = Z_{VY} Z_{YY}^{-1} \tag{37}$$

$$\widehat{V}_{t|t} = \widehat{V}_{t|t-1} + K_t(V_t^{ref} - \widehat{Y}_{t|t-1}) \tag{38}$$

$$Z_{t|t} = Z_{t|t-1} - K_t Z_{YY} K_t^{T} \tag{39}$$

Now sigma points are again calculated as shown by equations (24), (25) & (26). Hence, the cycle continues until the desired output is obtained.

4. SYSTEM CONFIGURATION AND SETUP

For implementation purpose a multi crystalline 22 V_{mp} & 1.3A I_{mp} solar panel is used with dimension of 655 mm X 296 mm X 35 mm. It produced 28.6 W at 25^0C and 1kW/m^2 irradiance. MPP varies from 18 V – 21.7 V depending upon environment conditions. The experimental setup along with solar panel is shown in Fig. 5.

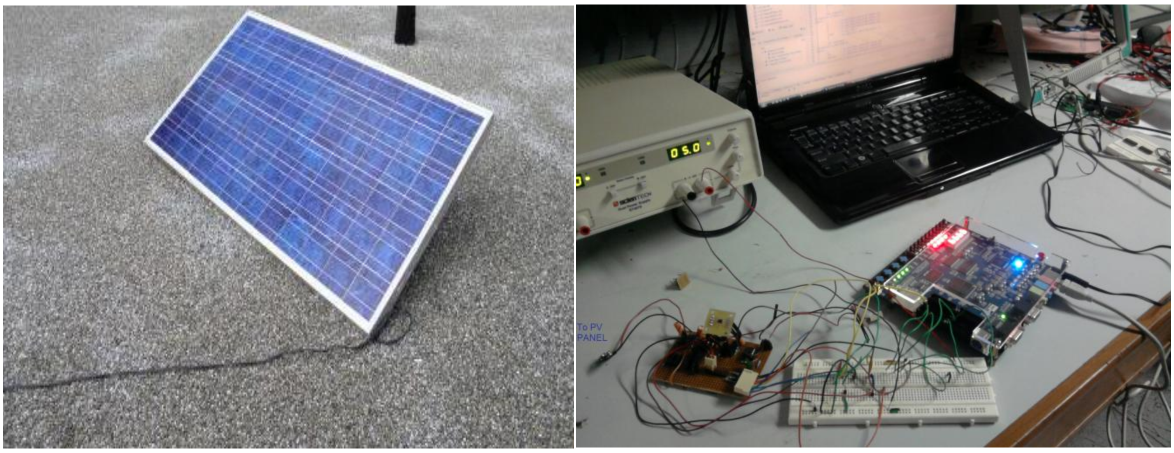

Figure 5. Experimental setup

As shown in Fig. 6, solar array is initially connected to current and voltage sensor which gives the voltage and current value at that instant of time, the voltage will be reduced between 0 – 5 V by using resistances so that it can be passed by a low pas filter to ADC (which works between 0 – 5 V). The digital output of ADC is sent to the FPGA running the MPPT algorithm for floating point values. The output from FPGA is sent to a Digital to Analog converter in form of the PWM wave, the Pulse width is decreased till one move closer to MPP and as one starts moving away from MPP the width of PWM is increased. The analog output is sent to DC - DC boost converter which converts voltage at levels 0 V – 5 V to appropriate level between 18 V – 24 V and thus final output is sent to the load connected. Fig.7. displays the circuit setup with the ICs used.

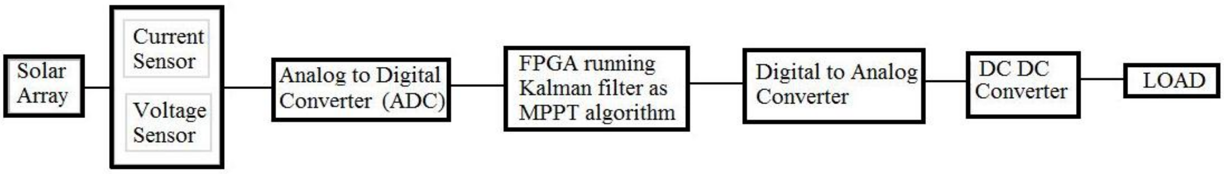

Figure 6. System setup (Block level)

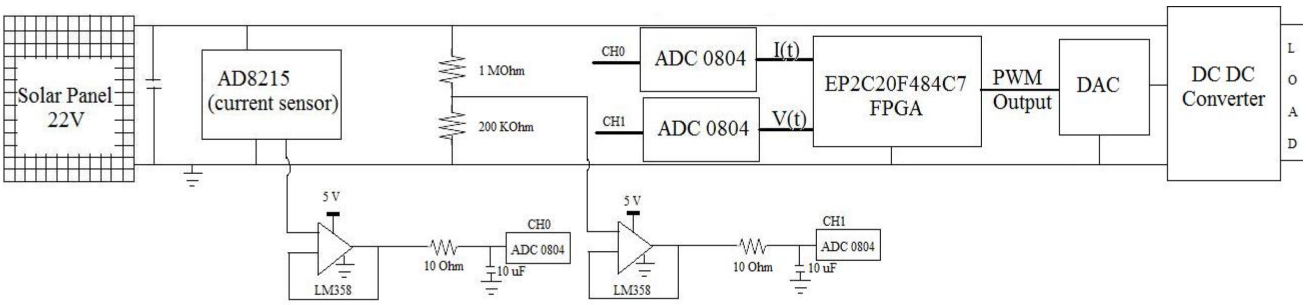

Figure 7. System setup with configuration (circuit level)

5. RESULTS AND DISCUSSION

The error approximation of current sensor is around ± 0.3% so an error of approximately 0.3% is considered from this when measuring current values. Voltage sensor has small accuracy issue but major accuracy issue comes with ADC which has error approximation of ± 2%. So, we take the measurement noise v to be around 2%. M (as referred in equation 10 and 16) is selected on the basis of voltage change limitation and slope of the P – V curve. According to calculation M comes out around 0.05. The algorithm has been realized on EP2C20F484C7 as implementation on reconfigurable architecture like FPGA ensures hardware based flexibility.

5.1. EXPERIMENTAL RESULTS WITH LINEAR KALMAN FILTER

Fig. 8 depicts the convergence of proposed MPPT algorithm at optimal conditions (i.e. 25^{0}C and 1kW/m^2) with the time of convergence around 4.5 ms. Simulation has been carried out using MATLAB 2009 according to power shown in Table 2.

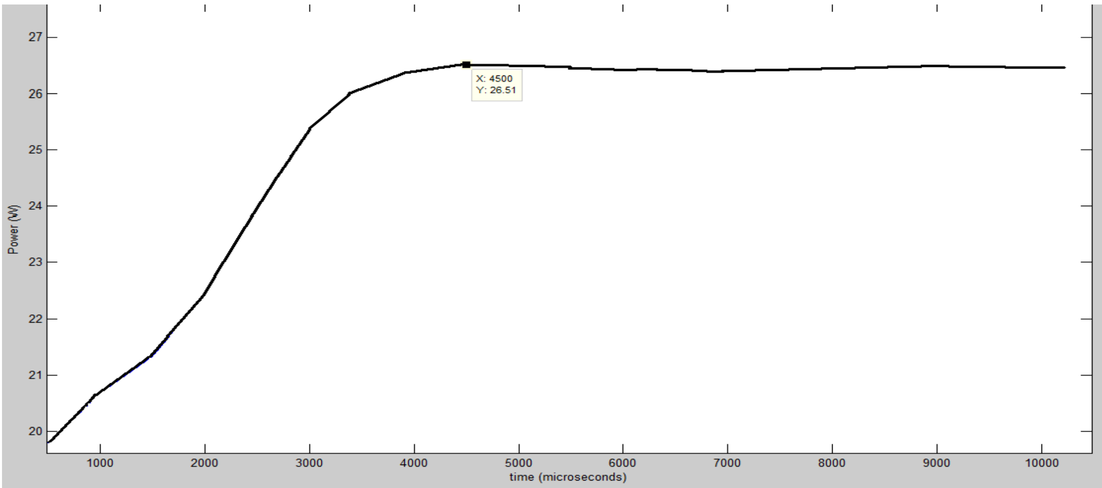

Figure 8. Convergence of proposed algorithm at 1kW/m^2 irradiance and T = 25^{0}C.

Table 1. Voltage and Power at falling irradiance level (Implementation done on a cloudy day)

Voltage		Current	Power
Actual(V)	MPPT(V)	A	MPPT(W)
20.61	20.76	0.94	19.52
20.33	20.62	1.00	20.62
20.20	20.43	1.03	21.05
19.97	20.30	1.06	21.52
19.85	20.21	1.05	21.22
19.66	20.10	0.82	16.48
19.52	20.02	0.68	13.62
19.46	19.97	0.55	10.98
19.30	19.88	0.52	10.34

Table 2. Result of the proposed MPPT algorithm under optimal conditions

Voltage		Current	Power		Efficiency (MPPT Power w.r.t Optimal Power)
Optimal(V)	MPPT(V)	A	Optimal(W)	MPPT(W)	%
21	21.38	1.19	27.3	25.44	93.19
	21.44	1.20		25.73	94.25
	21.48	1.22		26.21	96.01
	21.38	1.24		26.51	97.11
	21.44	1.22		26.16	95.82
	21.36	1.21		25.41	93.08

Using the proposed algorithm tracking of MPP under falling irradiance level is presented in Table 1.

From the Table 2 it is evident that the maximum power point has been tracked by the linear kalman filter with an efficiency of 97.11%. This is improvement over the tracking efficiency of 96.13% that has been achieved using P&O algorithm under similar conditions [14].

Fig.9 depicts the overall RTL of the proposed MPPT algorithm. The 8 bit S_{out} from the output is send to PWM generating module.

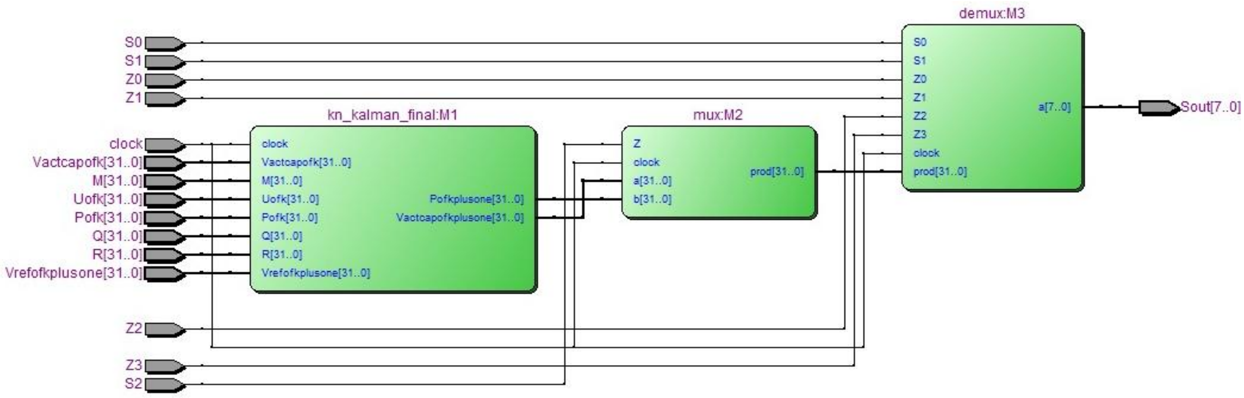

Figure 9. Post mapping RTL of proposed algorithm

Total logic elements utilized by Linear Kalman filter algorithm are 3723.

5.2. EXPERIMENTAL RESULTS WITH UNSCENTED KALMAN FILTER

This algorithm utilizes much more resources as compared to linear kalman filter algorithm & the no. of pins is insufficient on the FPGA board used for implementation of this algorithm so implementation is done module by module on the same Cyclone II FPGA.

Fig.10. depicts the convergence of the unscented kalman filter algorithm under optimal conditions (i.e. 25^0C and $1kW/m^2$) with the time of convergence around 11 ms. Simulation has been carried out using MATLAB 2009 according to power calculated in Table 4.

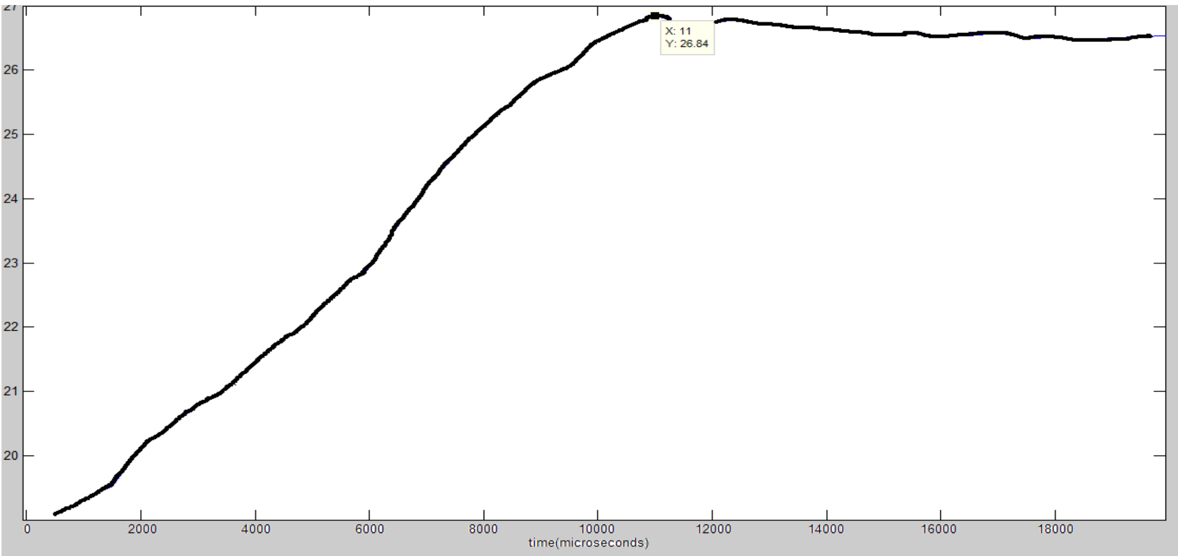

Figure 10. Convergence of proposed algorithm at $1kW/m^2$ irradiance and T = 25^0C.

Using the Unscented Kalman filter algorithm for MPP tracking the results for tracking of maximum power point under falling irradiance level is shown by Table.3. Table.4 is similar to Table.2 which depicts the efficiency of the algorithm to track maximum power point under optimal conditions.

Table.3. Voltage and Power at falling irradiance level (Implementation done on a cloudy day)

Voltage		Current	Power
Actual(V)	MPPT(V)	(A)	MPPT(W)
20.61	20.94	0.94	19.68
20.33	20.82	1.00	20.82
20.20	20.70	1.03	21.32
19.97	20.51	1.06	21.74
19.85	20.37	1.05	21.39
19.66	20.22	0.82	16.59
19.52	20.19	0.68	13.73
19.46	20.10	0.55	11.06
19.30	20.02	0.52	10.42

Table.4. Result of the proposed MPPT algorithm under optimal conditions

Voltage		Current	Power		Efficiency (MPPT power w.r.t Optimal Power)
Optimal(V)	MPPT(V)	(A)	Optimal(W)	MPPT(W)	%
21	21.75	1.19	27.3	25.88	94.81
	21.71	1.20		26.05	95.43
	21.70	1.22		26.47	96.97
	21.64	1.24		26.84	98.29
	21.67	1.22		26.44	96.84
	21.69	1.21		26.25	96.15

From Table 4 it is clear that maximum power point has been tracked by the unscented kalman filter with an efficiency of 98.29% which is even more than efficiency obtained with linear kalman filter.

As, the RTL of Unscented Kalman is big, it is divided into 3 sections which are shown in Fig.11, Fig.12, Fig.13. The final output depicted from Fig.11 is send to the PWM generating module which is similar to that of Linear Kalman.

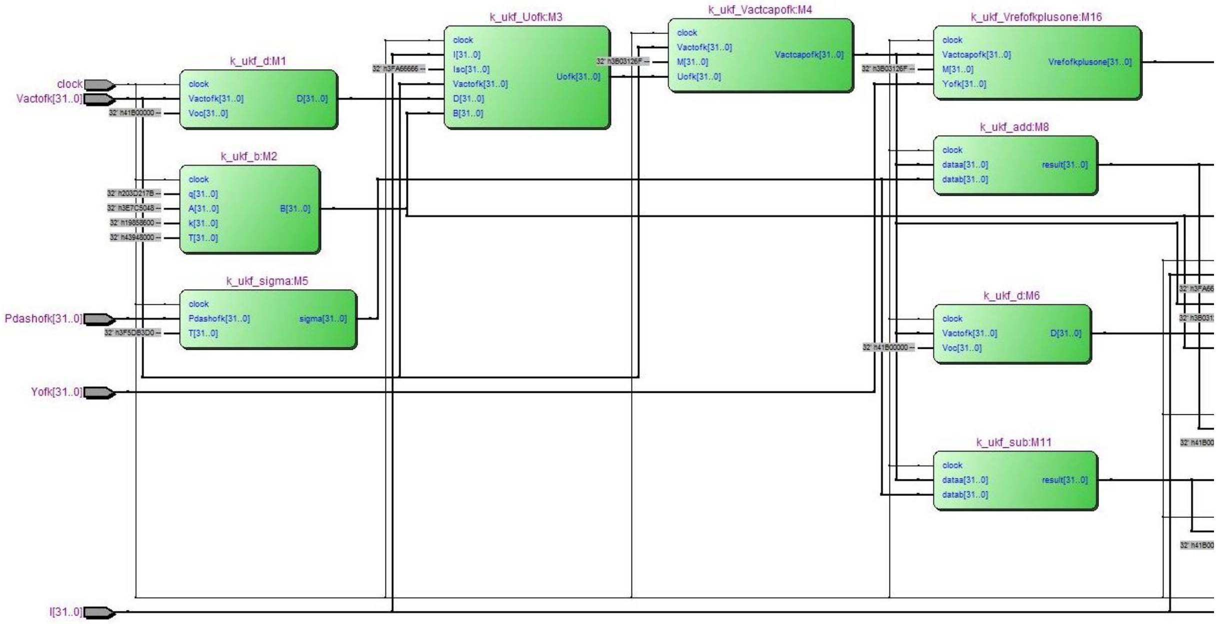

Figure 11. Section 1 of Post mapping RTL of unscented kalman filter algorithm

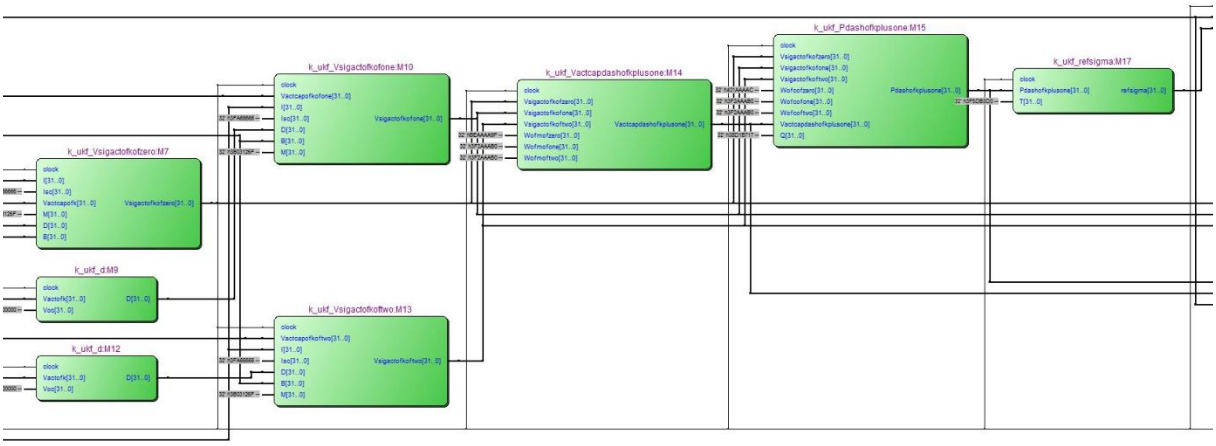

Figure 12. Section 2 of Post mapping RTL of unscented kalman filter algorithm

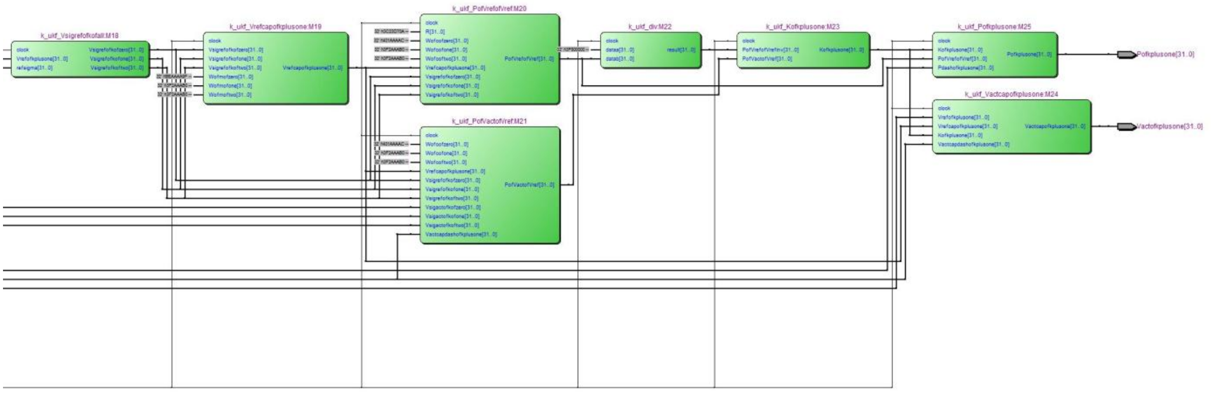

Figure 13. Section 3 of post mapping RTL of unscented kalman filter algorithm

Total logic elements utilized by Unscented Kalman filter algorithm are 34,187.

6. CONCLUSION

In this paper maximum power point tracking algorithm using 2 versions of Kalman filter has been proposed and is implemented on FPGA. The proposed methods perform estimation as fast as the clock rate of FPGA. Also, the FPGA implementation is very useful due to the fact that FPGA are reconfigurable and are becoming economical, faster and power efficient day by day. The Linear Kalman filter technique utilizes 3,723 logic elements which is really less as compared to the logic elements used by Unscented Kalman Filter approach. The time required for convergence to the maximum power point comes around 4.5 ms using the Linear Kalman filter technique which is much less than using Unscented Kalman filter approach which comes out to be 11 ms. However, the most important benefit provided by Unscented approach is the maximum power point tracking efficiency which comes around 98.3% as compared to 97.1% for case of Linear Kalman filter technique. It can also be concluded that both these approaches are better than generic P&O algorithm approach which is only 96% efficient and takes 15 ms [13] to converge to maximum power point. Further works can be done to improve the convergence rate and also the tracking efficiency under partially shaded conditions.

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